HERDING BEHAVIOUR IN STRATEGIC STYLE ALLOCATIONS: EMPIRICAL EVIDENCE ON UK PENSION PLAN MANAGERS

Laura Andreu* landreu@unizar.es +34 976 762308

Junior Lecturer in Finance

Cristina Ortiz cortiz@unizar.es +34 976 761000 Ext. 4652

Junior Lecturer in Finance

José Luis Sarto jlsarto@unizar.es +34 976 762308

Senior Lecturer in Finance

** Accounting and Finance Department*

Faculty of Economics and Business Studies

University of Zaragoza (Spain).

HERDING BEHAVIOUR IN STRATEGIC STYLE ALLOCATIONS: EMPIRICAL EVIDENCE ON UK PENSION PLAN MANAGERS

Abstract

This study firstly examines herding behaviour in the strategic style allocations of UK pension plans by using the traditional measure developed by Lakonishok *et al.* (1992). Afterwards, some original analyses are carried out to overcome certain shortcomings and limitations existing in this metric. The results show that UK pension managers are involved in herd behaviour although the magnitude of this phenomenon is reduced after the application of our alternative approach. Furthermore, this phenomenon is also confirmed when using additionational analyses to test this behaviour from other perspectives.

Key words: Herding Behaviour, Intertemporal Herding, Pension Plans, Strategic Style Allocations.

1. Introduction.

The increasing importance of institutional managers on stock markets has encouraged the research on the influence their trading exerts on asset prices. This interest is due to the belief that institutional herding behaviour[1] may have consequences on financial markets stability. A number of theoretical models have been suggested to explain this phenomenon; see, e.g. Bikhchandani and Sharma (2000) and Hirshleifer and Teoh (2003) for an exhaustive review of herding behaviour in capital markets. Empirical studies have focused on the behaviour of investment funds in the US market using the herding measure proposed by Lakonishok *et al.* (1992). These empirical analyses show that the actual extent of herding by institutional managers is modest when analysing portfolio holdings (see e.g., Grinblatt *et al*., 1995; Wermers, 1999; and Borensztein and Gelos, 2000).

Although recent literature reports the growing importance of pension funds for the domestic stock markets, the majority of the studies have focused on the behaviour of investment fund managers. Some exceptions are, for instance, the studies of Lakonishok *et al.* (1992) and Jones *et al.* (1999). Specifically, the pioneering study of Lakonishok *et al.* (1992) develops a herding metric (LSV henceforth) to investigate the holdings of more than 700 US pension funds, concluding that pension fund herding in large stocks is modest. Jones *et al.* (1999) report that US pension fund managers act as feedback traders especially on the buy side and mostly in small stocks with a high past performance. Similarly, Badrinath and Wahal (2002) also claim that US pension managers are engaged in feedback trading to a lesser extent than other institutions.

[1]Financial literature defines "herding" as the simultaneous trend of managers to buy or sell a particular stock in a given time period relative to what could be expected if managers trade independently.

Pension funds have also been analysed in other developed markets such as UK due to the increasing importance of this investment vehicle for individuals to ensure an appropriate income at retirement. Specifically, De Bondt and Forbes (1999) analyse herding behaviour in analyst' forecasts using data of UK companies between 1986 and 1997. On the other hand, Hwang and Salmon (2001) propose a herding measure based on the cross-sectional dispersion of factor sensitivity of assets. Specifically, these authors analyse the US, UK and South Korean stock markets during the period 1990-2000, finding that herding toward the market portfolio arises during relatively quiet periods rather than when markets are under stress. Later, Wylie (2005) analyses herding behaviour using the traditional LSV measure on the portfolio holdings of 268 UK equity mutual funds in the period 1986-1993. The study shows that the herding level is higher for the smallest stocks as was found by Lakonishok *et al.* (1992) and Wermers (1999).

The abovementioned empirical studies examine institutional herding behaviour of US and UK managers by analysing portfolio holdings. However, little is known about this behaviour when considering strategic style allocations althought the investment policy is one of the most relevant decisions of portfolio management, especially when analysing pension plans (see, Ibbotson and Kaplan, 2000). For that reason, this paper firstly investigates the herding behaviour in the strategic style allocations of UK personal pension plans in the period 2000-2007.

The analysis of herding in strategic style allocations is based on return data, being this information more available than portfolio holdings. Retuns are usually collected with higher frequency than portfolio holdings which make easier the detection of the behavioural patterns followed by managers.[2] Therefore, our research is also motivated by the ongoing studies that analyse herding behaviour considering portfolio holdings compared to the lack of conclusions about herding behaviour in strategic style allocations. As far as we know, this study is the first attempt to formally analyse herding behaviour of UK pension plans through the use of style allocations.

Our analysis of UK pension plans is also justified by the importance of the British market with respect to the rest of the markets in general and to the European industry in particular. Concretely, global pension statistics shown by *OECD* (2007) point out that UK is a mature market according to the ratio of pension assets relatively to the *GDP* of the economy.

Initially, the traditional LSV measure was applied to this dataset, finding levels of herding higher than those previously observed in the above studies using portfolio holdings. Although new procedures to test herding behaviour have been proposed (see, e.g. Hwang and Salmon, 2001, among others), LSV measure is still the most used in financial literature focused on institutional behaviour. After the application of the LSV measure, we explore whether these results are meaningful given the biases that Oehler (1998) and Wylie (2005) attribute to the traditional approach. The study of the shortcomings highlighted by these authors leads us to propose an alternative approach to capture the herding level more precisely as demonstrated in a simulation analysis. Hence, we contribute to financial literature by means of our attempt to improve the traditional method of detecting herding behaviour.

[2]Moreover, it is important to note that some research lines (e.g. window dressing) have shown that, sometimes, managers follow certain practices to disguise the actual portfolios hold.

Finally, we also tackle the limitations of the traditional measure pointed out by Bikhchandani and Sharma (2000) through the use of the amount ratio and a time-series analysis. The findings of these additional studies are consistent with those obtained by the traditional measure. Consequently, we add to financial literature given that we study the herding phenomenon from different perspectives.

The remainder of the paper is structured as follows: Section 2 introduces the UK pension market and our pension plan database. Section 3 explains the methodology used for measuring herding behaviour in strategic style allocations. Section 4 presents the empirical results obtained by applying the traditional herding measure and our alternative approach to solve some of its shortcomings. Section 5 includes some additional analyses to test this phenomenon from different perspectives and to raise alternatives to some limitations of the traditional metric. Finally, conclusions are summarised in Section 6.

2. Data

This paper analyses herding behaviour in strategic style allocations of UK pension plan managers. We used monthly data on the returns of 260 UK balanced pension plans that exist in the period from June 2000 to December 2007.[3] The dataset is free of survivorship bias, a relevant feature given that the consideration of only those funds that survived could create an illusion of herding as indicated by Wylie (2005). This information was obtained from Micropal, a company leader in providing independent information on mutual funds and pension schemes.

[3] The requirement of at least 36 observations to estimate robust parameters leads to a final sample of 193 balanced pension plans.

The analysis of the strategic style allocations of the pension plans included in our sample forces us to collect monthly returns of a series of benchmarks representative of the main holdings of these portfolios. These benchmarks are initially split in equity, fixed-income and cash indexes. This information was obtained from Morgan Stanley Capital International-Barra (MSCI-Barra) in the case of equity benchmarks and from the Bank of England in the case of fixed-income and cash indexes.

Table 1 provides descriptive statistics of the monthly returns and volatility (measured by the standard deviation) of the UK pension plans analysed along with the information of the whole spectrum of benchmarks initially considered.

Table 1. Descriptive statistics

The table shows some descriptive statistics for our sample of 193 UK balanced pension plans and for the different benchmarks initially proposed. The data is reported in monthly terms considering the entire period of analysis (June 2000-December 2007).

Pension Plans	Mean	Median	25th Percentile	75th Percentile	Standard Deviation
Equally-weighted portfolio	0.0033	0.0104	-0.0115	0.0227	0.0302
Number of pension plans	173	183	157	193	-
Benchmarks	Mean	Median	25th Percentile	75th Percentile	Standard Deviation
MSCI UK	0.0038	0.0106	-0.0137	0.0283	0.0359
MSCI Europe	0.0044	0.0099	-0.0168	0.0326	0.0440
MSCI USA	-0.0006	0.0052	-0.0214	0.0254	0.0452
MSCI Japan	-0.0013	-0.0008	-0.0343	0.0305	0.0520
MSCI World Index	0.0014	0.0092	-0.0214	0.0303	0.0419
10-year Fixed-Income	0.0038	0.0038	0.0036	0.0040	0.0003
5-year Fixed-Income	0.0039	0.0038	0.0036	0.0041	0.0004
3-year Fixed-Income	0.0038	0.0038	0.0035	0.0041	0.0004
1-year Fixed-Income	0.0037	0.0037	0.0034	0.0041	0.0005
1-month Treasury Bill Repos	0.0038	0.0037	0.0032	0.0042	0.0006

3. Methodology

3.1 The traditional LSV herding measure

The main aim of the paper is to determine whether UK pension plan managers are engaged in herding behaviour when they decide their investment style allocations. For that reason, we firstly use the well-known herding measure developed by Lakonishok *et al.* (1992) given that its generalised application makes easier the international comparability of the empirical findings.

According to this measure, herding is the simultaneous trend of managers to buy or sell a particular stock in a given time period relative to what could be expected if managers trade independently. Therefore, in the context of our study, herding is identified as the tendency of pension plan managers to change a specific style allocation in the same direction (increase or decrease) in a given period. In other words, there is herding behaviour when the proportion of managers that increase (reduce) a style allocation in a specific benchmark is above the expected proportion under the null hypothesis of independent management decisions. Therefore, positive and statistically significant values of the metric will provide evidence of herding behaviour. Concretely, the LSV measure defines herding for a given style j in a given period t, $H(j,t)$ as follows:

$$H(j,t) = \left| p(j,t) - p(t) \right| - AF(j,t) \tag{1}$$

where:

$$p(j,t) = \frac{B(j,t)}{B(j,t) + S(j,t)} \tag{2}$$

$$p(t) = \frac{\sum_{j=1}^{k} B(j,t)}{\sum_{j=1}^{k} B(j,t) + \sum_{j=1}^{k} S(j,t)} \tag{3}$$

$$AF(j,t) = E\big[\left|p(j,t) - p(t)\right|\big] \tag{4}$$

B(j,t) and *S(j,t)* is the number of managers who increase and decrease their exposure in the strategic style *j* over period *t* (net buyers and net sellers), note that these expressions follow a binomial distribution with probability *p(t)*; *p(j,t)* is the percentage of buying managers in style *j* in period *t*; *p(t)* is the expected proportion of managers buying in that period relative to the number of active managers aggregated across all styles and *AF(j,t)*, the adjustment factor calculated under the assumption that trades follow a binomial distribution with *B(j,t)* and *S(j,t)* as success and failure outcomes.

3.2 The style analysis model

Due to our analysis of herding behaviour in strategic style allocations, we have to determine these allocations in UK balanced pension plans. In order to do that, we use an index model based on the style analysis proposed by Sharpe (1992).

In this sense, to measure the performance of common stock funds, Elton *et al.* (1996) recommend a four-index model. This model includes the S&P 500 index, a size index, a growth versus value index, and one bond index. Afterwads, Elton *et al.* (1999) use the difference between the large-cap and the small-cap portfolios and the difference between the growth and value portfolios in addition to the S&P 500 index. These portfolios are correlated with the Fama and French (1993) size and book to market factors and capture the major limitations of the single-factor capital asset pricing model. Moreover, these portfolios span the major groups of stocks in which pension plans invest.

With regard to fixed-income benchmarks, Sharpe (1992) does not only use a government bond index but also includes corporate bond indices in the factor model that uses for style analysis. Similarly, Fama and French (1993) illustrate that a bond model should include factors related to bond maturity risk and bond default risk. In their study, Blake *et al.* (1993) propose, among other alternatives, a six-factor model including corporate and government bond indices that represent various maturities, a high-yield corporate bond index, and a mortgage-backed securities index. Additionally, Comer (2006) develops a new model to measure the bond portion of US hybrid funds since several funds do not show sensitivity to any of the bond indices proposed by Blake *et al.* (1993).

Although the performance of US benchmarks is not always strongly correlated due to the width of this market, the multicollinearity between the benchmarks in other markets is an important issue.[4] Table 2 reports the analysis of multicollinearity based on Pearson's correlation coefficients for the benchmarks initially considered to collect the main groups of assets in which UK balanced pension plans invest. Concretely, we have considered several equity benchmarks to account for the most important markets of investment (UK, Europe, USA, Japan and World) as well as fixed-income benchmarks to account for different maturities (10-year period, 5-year period, 3-year period and 1-year period) and a benchmark representative of cash (1-month Treasury Bill Repos).

[4] Some concerns about possible distorted results because of multicollinearity problems of the benchmarks were pointed out by Buetow *et al.* (2000) and Ben Dor *et al.* (2003). Hence, the selection of the appropriate benchmarks is of utmost importance.

Table 2. Pearson's correlation coefficients

	MSCI UK	MSCI Europe	MSCI USA	MSCI Japan	MSCI World	10-y FI	5-y FI	3-y FI	1-y FI	Repos
MSCIUK	1	0.955	0.832	0.447	0.899	-0.135	-0.119	-0.088	-0.028	-0.028
MSCIEurope		1	0.859	0.465	0.932	-0.166	-0.142	-0.109	-0.043	-0.041
MSCIUsa			1	0.522	0.974	-0.133	-0.119	-0.092	-0.035	-0.018
MSCIJapan				1	0.615	-0.233	-0.239	-0.211	-0.156	-0.160
MSCIWorld					1	-0.172	-0.155	-0.123	-0.055	-0.043
10-y FI						1	0.905	0.808	0.585	0.332
5-y FI							1	0.980	0.845	0.617
3-y FI								1	0.926	0.724
1-y FI									1	0.911
Repos										1

On the basis of the correlation results of Table 2 and bearing in mind the requirements of Sharpe's style analysis about the exhaustivity, exclusivity and independence of the benchmarks, we define a three-factor model to represent the expected return for a given balanced pension plan. Concretely, the high value of Pearson's coefficients between the different equity benchmarks analysed leads us to test the correlation between the returns of UK balanced pension plans and these indices in order to determine the equity benchmark of our model. Based on these results, we decide to use MSCI World index given that this benchmark seems to be the most relevant in the portfolios of our sample. On the other hand, we choose the 10-year fixed-income index as representative of the bond part of the portfolios since this index shows the lowest correlation to cash. Therefore, the model is as follows:

$$R_t^p = \beta_0^p + \beta_1^p R_{\text{MSCIWorld,t}} + \beta_2^p R_{\text{10yPublicBonds,t}} + \beta_3^p R_{\text{Repos,t}} + \varepsilon_t^p \qquad (5)$$

where R_t^p is the gross return of pension plan *p* in month *t*; $R_{MSCIWorld,t}$ is the gross return on the MSCI World index in month *t*, $R_{10yPublicBond,t}$ is the gross return on the 10-year UK Public Debt index in month *t* and $R_{Repos,t}$ is the gross return of 1-month UK Treasury Bill

Repos in month t, β_j^p is the style weight of the basic asset class j (where j=1 to 3) of pension plan p, β_0^p is the part of the return that active management adds to the merely passive tracking of the style portfolio[5] and ε_t^p is the residual return not captured by the model.

After the definition of the model, the main issue is whether this model represents the return-generating processs of UK balanced pension plans. To test the effectiveness of this model, we use Sharpe's (1992) quadratic programming technique. This methodology is used to determine the average exposure of a pension plan p to the major asset classes. Hence, the best explanation for the return R_t^p is given by style weights β_j^p that minimise the residual variance of the model subject to two restrictions: 100% of the portfolio must be invested (portfolio constraint) and short sales are not allowed (positivity constraint). Therefore, using the time series of returns, we solve the following quadratic equation:

$$Min\sum_{t=1}^{T}(\varepsilon_t^p)^2 = Min\sum_{t=1}^{T}(R_t^p - (\beta_0^p + \beta_1^p R_{1t} + \cdots + \beta_j^p R_{jt} + \cdots + \beta_k^p R_{kt}))^2 \quad (6)$$

subject to $\sum_{j=1}^{k}\beta_j^p = 1 \qquad 0 \le \beta_j^p \le 1 \quad j=1, 2, ..., k$

3.3 Application of the traditional LSV herding measure to strategic style allocations

The next step of our study is focused on the evolution of the strategic style allocations over time. Therefore, we estimate the style weights of each pension plan p considering 36-month rolling windows. The comparison of the style weights allocated by each portfolio in two

[5] The tradicional style model proposed by Sharpe (1992) does not include a constant β_0. However, equation 5 following the approach developed by De Roon *et al.* (2004) and Harri and Brorsen (2004) includes the constant to take into account the added value of active management.

consecutive rolling windows allows us to investigate if managers are increasing or decreasing their exposure to a certain asset.

In this sense, althought the traditional LSV measure gauges herding without regard to the direction of the strategic movements, we divide this metric into buying herding and selling herding. Thus, we define a buying or selling pension plan *p* in a strategic style *j* if:

$$\left.\begin{array}{ll} \beta_{j,II}^{p} > \beta_{j,I}^{p} & \text{(buying)} \\ \beta_{j,II}^{p} < \beta_{j,I}^{p} & \text{(selling)} \end{array}\right\rbrace \qquad (7)$$

where $\beta_{j,I}^{p}$ is the allocation in style *j* of pension plan *p* calculated over window I and $\beta_{j,II}^{p}$ is obtained from monthly returns over the next window (window II).

This rolling window approach implies overlapping data. Given that our dataset is composed of monthly observations, we consider monthly gaps for consecutive windows, deleting the first observation and adding the observation of the next period. Harri and Brorsen (2009) justify the use of overlapping data to estimate multi-period changes in order to achieve greater efficiency in the sense that we use all the information available.

Nevertheless, we perform a Monte Carlo analysis in order to assess the possible bias caused by using overlapping data because the cross-sectional convergence of managers could be the result of the existence of common data in two consecutive rolling windows. Specifically, our Monte Carlo analysis involves the generation of 50,000 different portfolios under different scenarios to test if the variation (increase or decrease) of the exposure in a specific style allocation is independent. Therefore, we try to demonstrate that given the style exposure of a rolling window the exposure of the next window could be higher or lower than the previous one with the same probability. In other words, the variation of the exposures is independent of the data value in which two rolling windows differs. Otherwise, the majority of managers would have convergent behaviour.

Our Monte Carlo analysis confirms this indepence in the movements of the style exposures.[6] Therefore, the overlapping data is not causing a possible problem of spurious herding and we can continue with our study trying to improve the traditional measure according to the numerous shortcomings and limitations pointed out in previous studies.

3.4 Shortcomings of the LSV herding measure

The traditional herding metric has caused some controversy due to some shortcomings and limitations detected through time. Oehler (1998) shows that this measure causes some problems of interpretation. This author firstly claims that LSV measure is designed to capture buying herding although potential convergent patterns in the selling side are also relevant. Based on these criticisms, our study is focused on both buying and selling herding as previously explained (see expression 7).

Secondly, Oehler (1998) indicates that the parameter *p(t)* calculated according to the LSV metric (see expression 3) does not capture properly the herding level in each asset class. Therefore, we consider interesting to work out a *p(t)* value for each style given that, according to this author, “the p(t) adjustment leads to a lack of information because averaging procedure (across all stocks) does not allow to compare stock by stock separately”. This drawback might also be affecting to our analysis of style allocations and is connected with some additional concerns about the *p(t)* values pointed out by Wylie (2005).

[6] Concretly, our simulation process shows that in 98.43% of the cases we can accept the null hypothesis of independence in the equity exposure movements. Similarly, this percentage reachs a value of 97.92% and 98.79% for bond and cash exposures, respectively.

Concretely, Wylie (2005) focuses on the hypotheses about the value of *p(t)* in which LSV metric rests on. The author indicates that the probability to buy or sell a stock in a give period *t* could not be the same given that managers cannot undertake short sales and, therefore, only managers having an initial holding are able to sell it. Additionally, the probability of buying a certain stock seems also to be conditioned by the size of the initial holding in the stock.

The concerns of Oehler (1998) and Wylie (2005) about the values of *p(t)* lead us to check the possible existence of a relationship between the previous exposures and the probability of increasing (decresing) them in the next period. In our dataset, we find a high statistical significance in this relationship as can be observed in Appendix 1. This result justifies our calculation of *p(t)* values taking into account the strategic style allocation of the previous period. Note that the underlying idea about the impact of the previous exposure on the probability of increasing this style weight is even more important when analysing strategic style allocation than when using portfolio holdings given the positivity and portfolio constraints of the style model (see, equation 6).

The calculation of *p(t)* values accounting for the style allocation of the previous period can be tackled through both a parametric and a non-parametric regression. From our point of view, the use of a non-parametric method is more advisable since a parametric regression like that used in Appendix 1[7] could create a generated regressor bias. Note that the values of the independent variable are the style weights estimated and therefore, they include estimation errors.

[7] The parametric regression of Appendix 1 was used to demonstrate that the tendency shown by Figure 1 and 3 is statistically significant.

Hence, we propose the calculation of the *p(t)* values using a non-parametric kernel method given the utility of this method in case of unknown forms of the relationship between two variables, in our case, the probability of increasing the exposure to a certain asset and the previous exposure. Therefore, kernel method provides us the probability of increasing the exposure to equities, fixed-income assets and cash assigned to each value of β_1, β_2 and β_3. These probabilities are calculated from the exposures of each pension plan *p* in each rolling window and the information about whether each exposure is higher or lower than the allocation in the previous period.[8] A detailed description of this method is shown in Appendix 2.

Finally, Bickchandani and Sharma (2000) indicate two limitations of LSV measure. The first limitation is based on the fact that this measure only uses the number of managers on the two sides of the market, without any regard for the amount of stocks they buy or sell to assess the extent of herding. With respect to the second limitation, this metric could be used to evaluate the level of herding in a given period *t* from a cross-sectional point of view, but it cannot detect whether certain managers constantly tend to imitate others over time. Similarly to the criticisms of Oehler (1998) and Wylie (2005), the limitations of Bickchandani and Sharma (2000) also affect our study of herding behaviour in style allocations.

We agree with the comments of these authors, although we have to bear in mind that they pointed out two features that, being of great interest, do not fit the original aims of the traditional metric. Nevertheless, we will try to find solutions to these limitations in two complementary analyses carried out in Section 5.

[8] Note that this latter information is what allows us to define a pension plan as buying or selling (see equation 7).

4. Empirical results

4.1 Strategic style allocation results

Table 3 reports summary statistics of the distribution of the style allocations followed by UK balanced pension plans according to the style model proposed. Several findings are clear from this table. First, the model works well across the UK pension plan sample examined as indicated by the high mean R^2 coefficient (79.78%). Therefore, the model has strong explanatory power despite the constraints imposed by the quadratic programming method. Second, as stressed by Comer (2006), the results emphasise the importance of modeling the bond and cash portion of balanced portfolios. Concretely, the mean exposure in the fixed-income index and cash index is 13.82% and 17.82%, respectively. Nevertheless, the most important weight is shown by the equity style allocation (68.36%), a result consistent with the investment goal of these portfolios.[9]

Table 3 – Summary statistics of Sharpe's style analysis

The table shows the estimated results from Sharpe's style analysis for our sample of UK balanced pension plans from June 2000 to December 2007. Each coefficient estimated represents the average exposure that each pension plan of the sample has allocated to each specific asset category. The R^2 coefficient reflects the explanatory power of the constrained regression. The figures report cross-sectional statistics of the pension plans of the sample.

	Mean	**Median**	**25th Percentile**	**75th Percentile**
β_0	0.0024	0.0023	0.0016	0.0030
β_1 (Equity)	0.6836	0.6811	0.6569	0.7085
β_2 (Fixed-Income)	0.1382	0.1456	0.0000	0.2661
β_3 (Cash)	0.1782	0.1663	0.0000	0.3248
R^2	0.7978	0.8230	0.7460	0.8600

[9] The *Investment Management Association* (IMA) indicates that the maximum equity exposure is restricted to 85% of the fund in balanced pension plans.

4.2 Herding results applying the traditional LSV measure

We start with the presentation of the standard herding results using the traditional LSV measure. Table 4 shows the results for both buying and selling herding as well as information on the number of months in which this phenomenon is observed in the sample. The results highlight an average herding level of 11.67%, a figure higher than those previously reported in the US market when examining pension plans' portfolio holdings (see, e.g. the level of 2.7% revealed by Lakonishok *et al*., 1992). Notwithstanding, the magnitude of herding shown by UK pension plans in relation to strategic style allocations is similar to that reported using portfolio holdings in other papers of less mature markets (see, e.g. the level of 22.6% shown in Voronkova and Bohl, 2005 for the Polish market). Additionally, from Table 4, we observe a higher herding behaviour in the equity style allocation (β_1), the most important asset in these portfolios. Note that this higher level of herding goes with a higher number of months in which this phenomenon is detected.

Table 4. Herding results based on the LSV measure.

The table shows the herding results of the LSV measure for both buying (BH) and selling (SH) managers as well as the aggregate level of herding (Average) for the different strategic style allocations analysed (equity, fixed-income and cash). The results for the whole time period analysed (June 2003-December 2007) are reported in the last column of the table. The figures report the herding level of each year in percentage terms as the average of the twelve months along with the number of months is which this behaviour is observed. Moreover, the confidence intervals of the herding levels appear below the metric. Herding measures in bold are statistically significant at 5% level.

	2003*	**2004**	**2005**	**2006**	**2007**	**2003-2007**
BH β_1	13.49 (5)	17.91 (5)	19.58 (5)	25.33 (8)	15.70 (7)	18.85 (30)
(Equities)	(9.45; 17.53)	(14.21; 21.61)	(16.16; 22.99)	(22.69; 27.98)	(12.98; 18.43)	(17.43; 20.27)
SH β_1	8.63 (2)	19.96 (6)	17.94 (7)	7.25 (4)	13.86 (4)	13.97 (23)
(Equities)	(2.12; 15.13)	(16.67; 23.26)	(15.01; 20.87)	(3.55; 10.94)	(10.31; 17.41)	(12.35; 15.59)
Average	11.06	18.94	18.76	16.29	14.78	16.41
	(7.62; 14.50)	(16.47; 21.41)	(16.52; 20.99)	(14.14; 18.44)	(12.60; 16.97)	(15.34; 17.48)
BH β_2	9.30 (3)	7.69 (3)	4.43 (6)	2.40 (2)	8.61 (5)	6.23 (19)
(Fixed-Income)	(3.07; 15.53)	(2.53; 12.85)	(-4.03; 12.90)	(-6.38; 11.18)	(3.91; 13.32)	(3.51; 8.95)
SH β_2	5.95 (3)	12.66 (8)	8.31 (6)	6.79 (6)	8.24 (5)	8.61 (28)
(Fixed-Income)	(-0.13; 12.03)	(9.59; 15.74)	(1.28; 15.34)	(0.54; 13.03)	(4.61; 11.88)	(6.63; 10.59)
Average	7.63	10.18	6.37	4.59	8.43	7.42
	(3.27; 11.99)	(7.52; 12.83)	(0.87; 11.88)	(-0.54; 9.73)	(5.51; 11.34)	(5.81; 9.04)
BH β_3	2.06 (2)	12.69 (9)	13.48 (6)	11.02 (4)	8.51 (5)	10.23 (26)
(Cash)	(-6.83; 10.94)	(8.84; 16.55)	(10.26; 16.70)	(7.18; 14.86)	(4.59; 12.43)	(8.43; 12.04)
SH β_3	9.21 (4)	7.13 (3)	10.90 (5)	20.96 (8)	11.31 (5)	12.15 (25)
(Cash)	(2.51; 15.91)	(5.94; 16.78)	(11.73; 14.48)	(10.24; 23.74)	(7.28; 15.89)	(8.72; 14.01)
Average	5.63	9.91	12.19	15.99	9.91	11.19
	(0.27; 10.99)	(6.32; 13.51)	(9.79; 14.59)	(13.73; 18.25)	(6.91; 12.91)	(9.89; 12.49)
Aggregate	8.11	13.01	12.44	12.29	11.04	11.67

**Although the return-based style analysis of Sharpe (1992) is carried out from June 2000 to December 2007, the use of 36-month rolling windows leads us to examine herding behaviour from June 2003 to December 2007. Therefore, in 2003 we can only consider seven months.*

4.3 Herding results applying an alternative approach

So far, herding results have been obtained applying the traditional LSV approach. Given that it is generally accepted that this metric presents some problems as discussed in the methodology section, we now propose a modification which provides more accurate estimates of the herding behaviour.

Our improvement to the traditional herding measure is based on the basic idea pointed out by Oehler (1998) and Wylie (2005) about the calculation of the probability of increasing the exposures. The problem is that the traditional metric does not take into account that this value could depend on the previous exposure, as we have demonstrated in our sample of UK balanced pension plans (see Appendix 1). Therefore, instead of using the *p(t)* values derived from expression 3, we propose the use of more accurate values of the probability of increasing the exposure to the different style allocations analysed. Specifically, to calculate these new *p(t)* values we use a non-parametric kernel method as explained in section 3.4 and Appendix 2.

Table 5 shows the herding level through the LSV metric but using the accurate values of the probability of increasing the different exposures obtained from the kernel's method. Similarly to Table 4, we report the results for both buying and selling herding as well as information on the number of months in which herding phenomenon is detected.

Table 5 is very illustrative since it seems to show more accurate results. This circumstance could be interpreted as an evidence of the superior suitability of our alternative approach as we will demonstrate in section 4.4. Concretely, the average herding level for the entire time period is reduced (9.83% instead of 11.67%). Moreover, it is important to stress that this decrease is observed in the herding level of the three style allocations.[10]

Table 5. Herding results based on our alternative approach

The table shows the herding results of the LSV measure for both buying (BH) and selling (SH) managers as well as the aggregate level of herding (Average) for the different strategic style allocations analysed (equity, fixed-income and cash) when using the probability values obtained from the kernel method. The results for the entire time period analysed (June 2003-December 2007) are reported in the penultimate column of the table. Additionally, the last column of the table shows the differences between the level of herding by applying the traditional LSV measure and the method proposed here of using more accurate values of *p(t)*. The figures report the herding level of each year in percentage terms as the average of the twelve months along with the number of months is which this behaviour is observed. Moreover, the confidence intervals of the herding levels appear below the metric. Herding measures in bold are statistically significant at 5% level.

[10] Note, however, that these differences are not statistically significant in all the investment styles.

	2003*	2004	2005	2006	2007	2003-2007	Gap
BH β_1 (Equities)	7.13 (4) (2.64; 11.62)	13.92 (5) (10.24; 17.60)	14.25 (5) (10.84; 17.66)	20.53 (8) (17.91; 23.16)	10.51 (7) (7.79; 13.23)	13.83 (29) (12.40; 15.26)	*5.02*
SH β_1 (Equities)	9.21 (2) (2.73; 15.69)	21.19 (6) (17.91; 24.47)	19.70 (7) (16.79; 22.61)	10.86 (4) (7.16; 14.55)	11.88 (4) (8.26; 15.50)	15.05 (23) (13.44; 16.67)	*-1.08*
Average	8.17 (4.48; 11.86)	17.56 (15.11; 20.01)	16.97 (14.76; 19.19)	15.70 (13.55; 17.84)	11.19 (9.02; 13.37)	14.44 (13.37; 15.51)	*1.97*
BH β_2 (Fixed-Income)	8.01 (2) (2.31; 13.71)	11.63 (3) (7.36; 15.90)			2.29 (1) (-4.20; 8.78)	4.06 (6) (1.03; 7.08)	*2.18*
SH β_2 (Fixed-Income)	4.09 (3) (-0.52; 8.71)	7.12 (9) (4.74; 9.50)	8.44 (12) (6.84; 10.04)	7.28 (11) (5.65; 8.91)	6.95 (11) (5.16; 8.75)	7.02 (46) (6.12; 7.92)	*1.59*
Average	6.05 (2.46; 9.64)	9.38 (7.30; 11.46)	8.44 (6.84; 10.04)	7.28 (5.65; 8.91)	4.62 (2.89; 6.35)	5.54 (4.67; 6.41)	*1.88*
BH β_3 (Cash)		4.65 (2) (-0.77; 10.06)	18.55 (6) (15.43; 21.67)	10.57 (4) (6.92; 14.22)	8.17 (4) (4.61; 11.73)	9.15 (16) (7.30; 11.00)	*1.08*
SH β_3 (Cash)	6.59 (5) (2.93; 10.25)	9.29 (10) (6.88; 11.54)	9.96 (6) (6.90; 13.02)	15.08 (8) (6.27; 17.65)	7.08 (8) (6.19; 9.33)	9.88 (37) (6.63; 11.06)	*2.27*
Average	6.59 (2.93; 10.25)	6.97 (4.88; 9.06)	14.26 (12.08; 16.44)	12.82 (10.72; 14.92)	7.63 (5.70; 9.56)	9.51 (8.51; 10.52)	*1.68*
Aggregate	6.94	11.30	13.22	11.93	7.81	9.83	*1.84*

**Although the return-based style analysis of Sharpe (1992) is carried out from June 2000 to December 2007, the use of 36-month rolling windows leads us to examine herding behaviour from June 2003 to December 2007. Therefore, in 2003 we can only consider seven months.*

4.4 Simulation analysis to compare the properties of the two herding measures

Once the results obtained by our alternative method have been shown, it is important to test whether this new approach really provides more precise calculations of the herding level. Consequently, we compare the properties of the new and the traditional measure in Monte Carlo simulations. In order to do that, we conduct a Monte Carlo analysis in which we generate 1,000 simulations of no expected herding with random betas.

Specifically, our simulation study considers the set of estimated betas for each pension plan and for each rolling window. Given this information, our simulation aims to covering a situation of no herding generating different scenarios in which each portfolio can show any value for the different exposures according to a random process. After that, we calculate the herding level with both the LSV measure and our alternative approach to test whether results confirm the situation of no herding or otherwise the measures show spurious herding.

Our Monte Carlo analysis shows that LSV measure captures herding when using betas simulated although no herding should be expected. Concretely, this measure leads to buying and selling herding in the three investment styles in 50.13% of the simulated scenarios. As a consequence, in half of the theoretical situations of no herding, the traditional metric captures this phenomenon. Additionally, we also observe that the traditional measure detects herding behaviour in 21.84% of the years.

On the contrary, the number of simulations showing positive and statistically significant levels of buying and selling herding is reduced to 26.60% in our alternative approach instead of 50.13%. Additionally, a significant reduction in the number of years in which this phenomenon is statistically significant is also observed (3.57% instead of 21.84%). Although herding phenomenon is still detected, the level has been dramatically reduced. Consequently, we can conclude that our analysis improves the traditional measure and provides, therefore, more accurate results of herding behaviour. In summary, the results of the Monte Carlo analysis confirm the efficiency of the new approach proposed.

5. Additional analyses

5.1 Herding results taking into account the amount of trades

Despite the popularity of the LSV measure, this metric presents some limitations given that the pioneer study of Lakonishok *et al.* (1992) only pays attention to the tendency of managers to trade in herds in a given period. However, there is also other information very relevant to test this phenomenon. Bearing in mind only the number of active managers and disregarding the value of their trades can overlook herding which can in fact be present.[11]

For that reason, some authors like Oehler (1998), Wermers (1999) and Voronkova and Bohl (2005) allege the use of a complementary measure that collects information about the amount of stocks bought or sold by each manager. This measure referred to dollar ratio and volume herding in financial literature is defined in our study of herding in strategic style allocations as amount ratio since it considers the magnitude or value of the increases or reductions in the strategic assignments of each period. The ratio is expressed as follows:

$$AmountRatio(j,t) = p(j,t) - p(t) \tag{8}$$

where

$$p(j,t) = \frac{B(j,t)}{B(j,t) + S(j,t)} \tag{9}$$

$$p(t) = \frac{\sum_{j=1}^{k} B(j,t)}{\sum_{j=1}^{k} B(j,t) + \sum_{j=1}^{k} S(j,t)} \tag{10}$$

B(j,t) and *S(j,t)* is the amount bought and sold in the strategic style *j* over period *t* instead of the number of managers that increase or decrease the style *j*; *p(j,t)* is the percentage of the amount bought in style *j* in period *t*; *p(t)* is the expected proportion of the amount bought in that period relative to the amount traded aggregated across all styles.

Similarly to the calculation of more accurate values of *p(t)* when using the LSV herding measure, we have considered the possibility of applying our alternative method to detect the intensity of the herding behavior. Notwithstanding, in this case, we fail to find a

[11] Think about a situation in which the buyers and sellers are similar in number but the buyers collectively demand a substantial amount of the stock while the sellers only put a relatively small amount into the market. In such a situation, even though herding into stocks exists, the LSV measure would not capture it.

statistical relationship between the previous values of the exposures and the magnitude of the subsequent variations as can be observed in Appendix 3. Hence, we focus our analysis on the application of the abovementioned ratio.

This ratio is quite similar to the LSV measure, with the sole difference being that instead of analysing the number of managers trading on the same side of the market, the above ratio considers the amount of trading carried out. Note that the amount ratio does not include the adjustment factor of the LSV metric given that, in this approach, the variables (the amounts bought and sold) are continuous.

The results obtained by considering this ratio are gathered in Table 6. As we could expect, this table provides evidence of herding behaviour from a quantitative perspective. Thus, this finding supports the results obtained by applying the traditional measure, demonstrating the complementarity of both perspectives.

Table 6. Herding results based on the amount ratio

The table shows the herding results based on the amount ratio for both buying (BH) and selling (SH) managers as well as the aggregate level of herding (Average) for the different strategic style allocations analysed (equity, fixed-income and cash). The results for the entire time period analysed (June 2003-December 2007) are reported in the last column of the table. The figures report the herding level of each year in percentage terms as the average of the twelve months along with the number of months is which this behaviour is observed. Moreover, the confidence intervals of the herding levels appear below the metric. Herding measures in bold are statistically significant at 5% level.

	2003*	2004	2005	2006	2007	2003-2007
BH β_1 (Equities)	10.76 (5) (6.74; 14.77)	15.36 (6) (12.07; 18.65)	17.26 (5) (13.83; 20.67)	21.69 (7) (18.88; 24.42)	13.14 (7) (10.42; 15.85)	16.08 (30) (14.66; 17.48)
SH β_1 (Equities)	7.72 (2) (1.38; 14.06)	15.53 (6) (12.31; 18.75)	18.29 (7) (15.37; 21.20)	8.71 (5) (5.41; 12.01)	9.16 (5) (5.92; 12.39)	12.26 (25) (10.73; 13.79)
Average	9.24 (5.80; 12.68)	14.32 (13.07; 17.82)	16.46 (15.54; 20.00)	16.43 (13.03; 17.33)	10.91 (9.05; 13.24)	14.34 (13.12; 15.22)
BH β_2 (Fixed-Income)	22.54 (4) (18.02; 27.07)	13.31 (5) (9.68; 16.94)	15.75 (6) (12.59; 18.91)	12.48 (5) (9.26; 15.70)	23.79 (8) (21.23; 26.36)	17.12 (28) (15.66; 18.59)
SH β_2 (Fixed-Income)	5.18 (3) (-0.10; 10.46)	20.97 (7) (17.84; 24.10)	20.65 (6) (17.50; 23.81)	18.58 (7) (15.69; 21.30)	12.84 (4) (9.21; 16.46)	16.59 (27) (15.07; 18.08)
Average	13.86 (10.42; 17.30)	17.14 (14.77; 19.51)	18.20 (15.97; 20.44)	15.53 (13.34; 17.64)	18.31 (16.22; 20.41)	16.86 (15.80; 17.90)
BH β_3 (Cash)	1.29 (3) (-3.99; 6.57)	25.23 (7) (22.10; 28.37)	16.32 (6) (13.16; 19.47)	19.19 (5) (15.90; 22.48)	12.25 (4) (8.62; 15.88)	16.09 (25) (14.52; 17.66)
SH β_3 (Cash)	21.69 (4) (17.17; 26.22)	17.40 (5) (13.77; 21.03)	10.39 (6) (7.22; 13.54)	26.07 (7) (23.33; 28.89)	27.18 (8) (24.62; 29.75)	20.44 (30) (19.04; 21.86)
Average	11.49 (8.05; 14.93)	21.32 (18.94; 23.69)	13.35 (11.11; 15.58)	22.63 (20.50; 24.80)	19.72 (17.62; 21.81)	18.27 (17.22; 19.32)
Aggregate	11.53	17.59	16.00	18.19	16.31	16.49

**Although the return-based style analysis of Sharpe (1992) is carried out from June 2000 to December 2007, the use of 36-month rolling windows leads us to examine herding behaviour from June 2003 to December 2007. Therefore, in 2003 we can only consider seven months.*

5.2 Herding results taking into account a time-series perspective

As mentioned by Bikhchandani and Sharma (2000), another limitation of the LSV measure is related to the fact that the traditional metric could be used to evaluate the herding level in a given period from a cross-sectional point of view, but it cannot detect whether certain managers constantly tend to imitate others over time (time-series perspective).

As a consequence, the study of Andreu *et al.* (2009) proposes a time-series analysis to test intertemporal herding patterns. Specifically, these authors compare the variations in the investments of each portfolio to those carried out by the other managers through an equally-weighted portfolio. This analysis attempts to distinguish whether some pension plans have herding behaviour over time. Applying this method to our analysis, we compute time-series regressions for each pension plan p is as follows:

$$\Delta\beta_{pj,t} = h_{pn} \cdot \Delta\beta_{nj,t} + e_{pj,t} \tag{11}$$

where $\Delta\beta_{pj,t}$ is the monthly variation in the strategic allocation of pension plan p in asset j in the period t, $\Delta\beta_{nj,t}$ is the monthly variation in the strategic allocation of the equally-weighted portfolio n that encompasses every pension plan expect p in asset j in the period t, h_{pn} is the slope of the regression and $e_{pj,t}$ is the residual term of the regression.

The slope of this regression indicates the convergence in the strategic changes on asset j allocated by each pension plan p and by the rest of the pension plans. A positive and statistically significant h_{pn} would provide evidence of intertemporal herding in the strategic allocations considered.

Table 7. Intertemporal herding results*

This table shows the number of pension managers engaging in intertemporal herding behaviour, whereas the numbers in brackets indicate the percentage of the sample that they represent. The average level of significance is calculated for every h_{pn} that presents a given sign.

		$h_{pn}>0$	*Average*	$h_{pn}<0$	*Average*
Significant	β_1 *(Equities)*	170 (100%)	0.0000	-	-
Not Significant	β_1 *(Equities)*	-	-	-	-
Significant	β_2 *(Fixed-Income)*	139 (81.76%)	0.0054	-	-
Not Significant	β_2 *(Fixed-Income)*	31 (18.24%)	0.3068	-	-
Significant	β_3 *(Cash)*	151 (88.82%)	0.0047	-	-
Not Significant	β_3 *(Cash)*	19 (11.18%)	0.2879	-	-

* Only those pension plans with at least 24 monthly variations are considered to obtain robust parameters. Specifically, we examine 170 balanced pension plans.

The results of intertemporal herding are shown in Table 7. This table shows a high number of pension managers with herding behaviour over time in relation to the rest of the portfolios analysed. We emphasise the high percentage of the sample (more than 80%) that show positive and significant $h_{in.}$ We also highlight that this value reaches 100% when the equity asset allocation is studied. Therefore, these results agree with those obtained using the LSV measure and the amount ratio, providing evidence for a global trend towards herding over time among the pension plans under study.

Nevertheless, these results should be taken with caution given that both the dependent and independent variables of equation 11 are estimated. Hence, they include estimation errors and could bias our findings. For that reason, we are committed to analyse the impact of this bias on the intertemporal herding magnitude. This study will be tackled in the near future through a Monte Carlo analysis.

6. Concluding remarks

This paper focuses on the herding behaviour of UK pension managers, an interesting field of research taking into account the actual influence of institutional managers on stock markerts. Specifically, we provide new insights into herding phenomenon by examining managers' decisions with regard to the evolution of their strategic style allocations.

We firstly use the well-known herding measure developed by Lakonishok *et al.* (1992), finding empirical evidence of herding behaviour among UK managers during the entire period. Afterwards, we try to contribute to the literature by proposing an alternative approach to overcome some shortcomings detected in this traditional measure. The results obtained are robust to those reported by the traditional metric although the reduction in the herding level and the effectiveness of this new approach must be highlighted.

Finally, we also evaluate the herding phenomenon from two aditionally perspectives in order to overcome two limitations detected in the traditional metric and to show a complete view of this behaviour. In these complementary analyses we find that the extent of herding phenomenon is in line with the level reported by the traditional measure and we demonstrate that this behaviour persists over time providing evidence of a very relevant intertemporal herding.

In order to test the possible existence of a relationship between the previous exposures and the increasing probability in the next period, we calculate the following equation for each style allocation *j*:

$$p(t) = a + b * \hat{\beta} + \varepsilon \tag{12}$$

Where *p(t)* is the probability to increase a specific style allocation given the prior value of this allocations, $\hat{\beta}$ is the estimated value of the style allocation analysed in the previous period and *a* and *b* are the intercept and the slope of the regression. The values of *p(t)* are calculated by grouping the exposures into intervals.

The aim pursued with this analysis is to test whether the movements (increases and decreases) in a style allocation depend or not on the previous exposures as suggested by Wylie (2005). The results obtained from this regression are reported in Table 8. From this table we can see that the slope of the regressions carried out are statistically different from zero in the case of the equity and cash exposures at 5% level whereas the slope of the fixed-income regression is very close to this significance level. Hence, the critiscim carried out by Wylie (2005) is confirmed in our dataset and we need to calculate accurate values of *p(t)* taking into account the information of the previous exposures.

Table 8. Relationship between the probability of increasing an exposure and its previous value

The table shows the results of equation 12 to test whether the probability of increasing the different style allocations analysed (equity, fixed-income and cash) depends on the previous value of these exposures.

	Intercept	**Slope**	R^2
β_1 *(Equities)*	0.9327 (0.7977; 1.068)	-0.5661 (-0.7704; -0.3617)	44.59%
β_2 *(Fixed-Income)*	0.3943 (0.3118; 0.4769)	-0.2601 (-0.5596; 0.0393)	6.37%
β_3 *(Cash)*	0.6539 (0.5839; 0.7240)	-0.6792 (-0.9753; -0.4975)	46.14%

Additionally to the results shown in Table 8, Figures 1, 2 and 3 illustrate graphically the values of the style allocation analysed in each figure and the probability of increasing this exposure in the next period. Specifically, Figures 1 and 3 show a clear tendency indicating that the probability of increasing the equity and cash exposures is inversely related to the prior value of the allocation. A finding consistent with the results reached in Table 8.

Figure 1 - Relationship between the probability of increasing the equity exposure (*p(t)* values*)* and the previous equity weight (β_1)

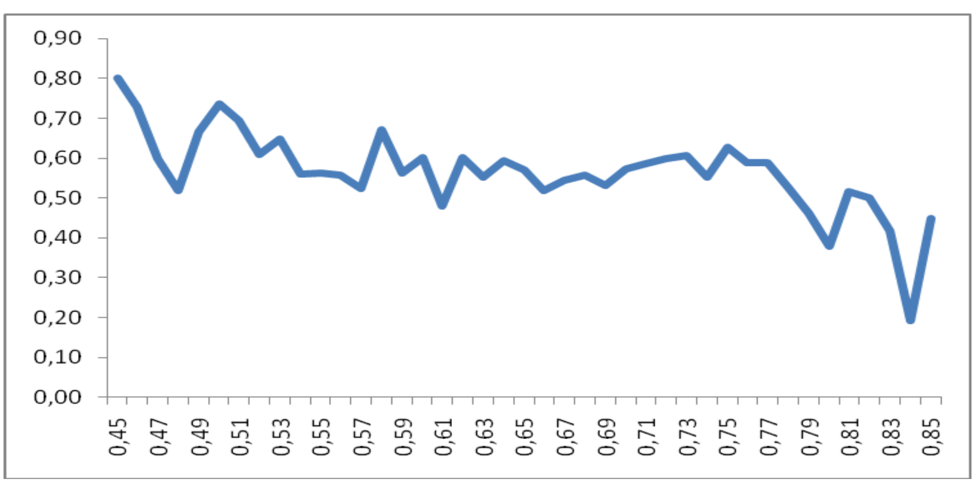


Figure 2 - Relationship between the probability of increasing the fixed-income exposure (*p(t)* values*)* and the previous fixed-income weight (β_2)

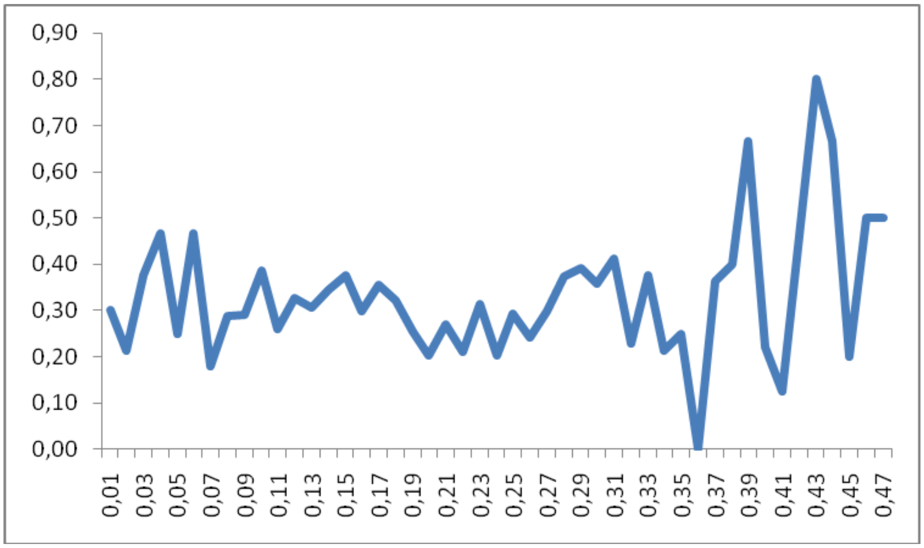
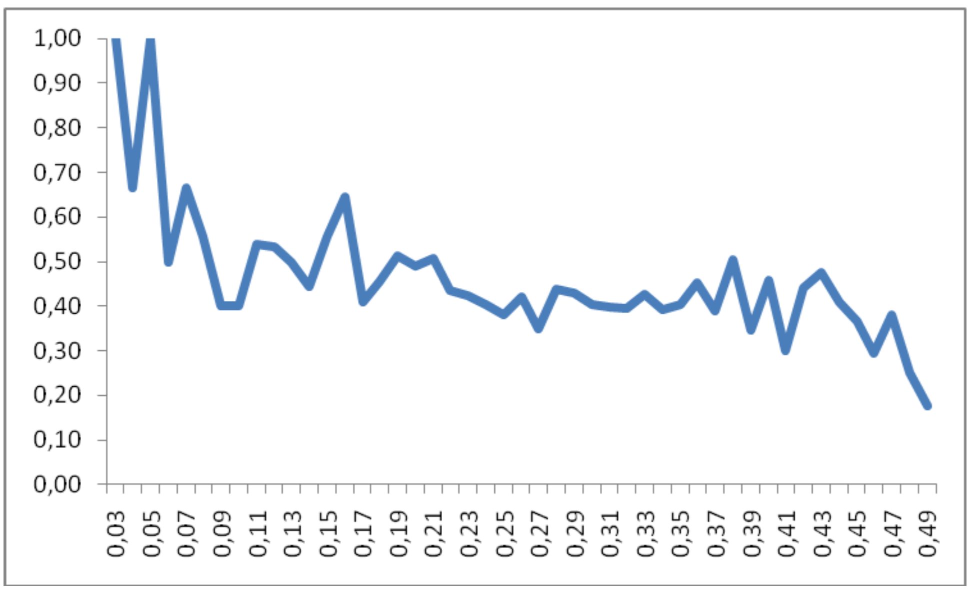


Figure 3 - Relationship between the probability of increasing the cash exposure (*p(t)* values) and the previous cash weight (β_3)



We propose a non-parametric regression to obtain a smooth approximation of the relationship between the probability of increasing the exposure to a certain style and the previous values of this style, in our case g(β_j), where *j*=1 to 3. This method only requires the the set of observations of the exposures of pension plans to a certain style *j* and the information about if these exposures have increased or decreased in the following period. Therefore, the non-parametric regression is as follows:

$$g(\beta_j) = p\left[I_t^p = 1 \mid \beta_{j,t-1}^p = \beta_j\right] \quad \text{where } \mathrm{I}_t^p = \begin{cases} 1 \text{ if } \beta_{j,t-1}^p < \beta_{j,t}^p \\ 0 \text{ otherwise} \end{cases} \qquad (13)$$

Concretely, non-parametric regressions aim at determining a decreasing function of distances from a β_j to calculate the weights associated to each location. The values close to that allocation receive more weight than those remote from it, which receive little or no weight. Given that gaussian kernel estimators are one of the most used non-parametric methods, we calculate it as follows:

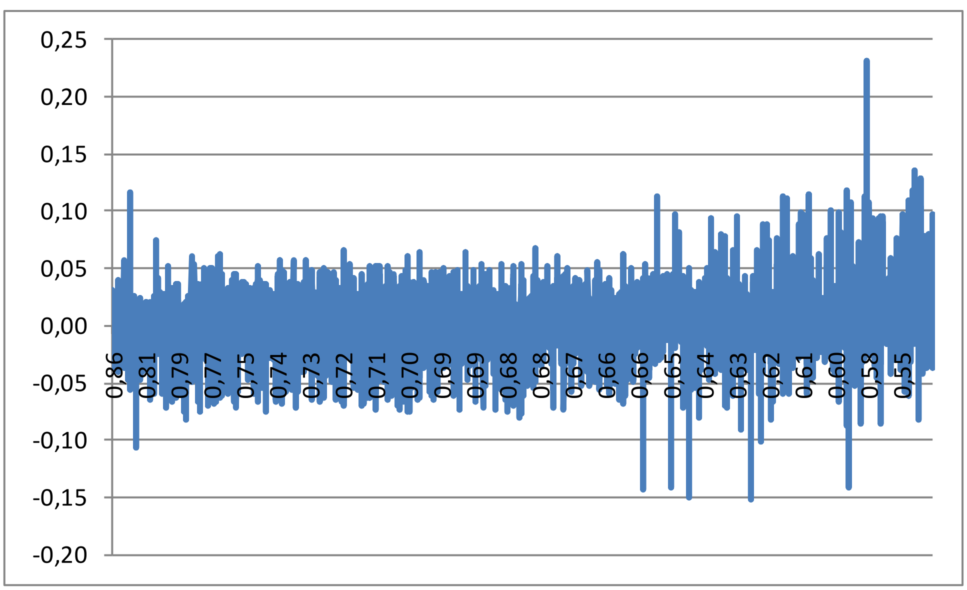
$$\hat{g}(\beta_j) = \frac{\sum_{p=1}^{N} \sum_{t=t_{\min,p}+1}^{t_{\max,p}} \hat{I}_t^p K\left(\beta_j; \hat{\beta}_{j,t-1}^p, h\right)}{\sum_{p=1}^{N} \sum_{t=t_{\min,p}+1}^{t_{\max,p}} K\left(\beta_j; \hat{\beta}_{j,t-1}^p, h\right)} \qquad \text{where } \hat{\mathrm{I}}_t^p = \begin{cases} 1 \text{ if } \hat{\beta}_{j,t-1}^p < \hat{\beta}_{j,t}^p \\ 0 \text{ otherwise} \end{cases} \qquad (14)$$

where:

K($\beta;\mu,\sigma$*)* is the value of density function of a N(μ,σ) distribution in the location β_j and allows us to determine the weights associated to each location.
h is the window width, also called the smoothing parameter or bandwidth
N is the number of pension plans {p = 1,…, N}. In our case N=193.
t refers to the time period considered {1≤ tmin,p < tmax,p ≤ T }, being tmin,p (tmax,p) the lower (upper) limit of the observed period of pension plan *p*. It is also important to bear in mind that each pension plan *p* presents different life periods.

Figure 4, similarly to Figure 1, shows graphically the relationship between the values of the equity exposure and the magnitude of the variation in these weights in the next period with the aim of testing the possible existence of a relationship between these two variables. As opposed to Figure 1, Figure 4 does not show any clear tendency indicating that the variation of the equity exposure (increases and decreases) does not depend on the prior value of this allocation. Similar results are also obtained when applying a parametric regression (see equation 12) as well as when analysing fixed-income and cash allocations.[12]

Figure 4 - Relationship between the magnitude of the movements of the equity exposure and the previous equity weight (β_1)



[12] These results are not provided for space reasons but are available upon request to the authors.

References

Andreu, L., C. Ortiz, and J. L. Sarto, 2009. “Herding behaviour in strategic asset allocations: New approaches on quantitative and intertemporal imitation”. *Applied Financial Economics*, 19(20), 1649-1659.

Badrinath, S. G., and S. Wahal, 2002. “Momentum trading by institutions”. *Journal of Finance*, 57(6), 2449-2478.

Ben Dor, A., R. Jagannathan, and I. Meier, 2003. "Understanding mutual fund and hedge fund styles using return-based style analysis", *Journal of Investment Management*, 1(1), 94-134.

Bikhchandani, S., and S. Sharma, 2000. "Herd behavior in financial markets", *IMF Staff Papers*, 47(3), 279-310.

Blake, C., E. Elton, and M. Gruber, 1993. “The performance of bond mutual funds”, *Journal of Business*, 66(3), 371-403.

Borenzstein, E. R., and R. G. Gelos, 2000. “A panic-prome pack? The behaviour of emerging market mutual fund”, *IMF Working Paper*, WP/00/198.

Buetow, G. W.,Jr, R. R. Johnson, and D. E. Runkle, 2000. "The inconsistency of return-based style analysis", *Journal of Portfolio Management*, 26(3), 61-77.

Comer, G., 2006. “Hybrid mutual funds and market timing performance”. *The Journal of Business*, 79(2), 771-797.

De Bondt, W. F. M., and W. P. Forbes, 1999. "Herding in analyst earnings forecasts: Evidence from the United Kingdom", *European Financial Management*, 5(2), 143-163.

De Roon, F. A., T. E. Nijman, and T. R. Ter Horst, 2004. "Evaluating style analysis", *Journal of Empirical Finance*, 11(1), 29-53.

Elton, E., M. Gruber, and C. Blake, 1996. “The persistence of risk-adjusted mutual fund performance”. *Journal of Business*, 69(2), 133–157.

———, 1999. “Common factors in active and passive portfolios”. *European Finance Review*, 3, 53–78.

Fama E. F., and K. R. French, (1993). “Common risk factors in the returns on stocks and bonds”. *Journal of Financial Economics*, 33(1), 3-56.

Grinblatt, M., S. Titman, and R. Wermers, 1995. "Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior", *The American Economic Review*, 85(5), 1088-1105.

Harri, A., and B. W. Brorsen, 2004. "Performance persistence and the source of returns for hedge funds", *Applied Financial Economics*, 14(2), 131-141.

Harri, A., and B. W. Brorsen, 2009. “The overlapping data problem”, *Quantitative and Qualitative Analysis in Social Sciences*, 3(3), 78-115.

Hirshleifer, D. and S. Hong Teoh, 2003. “Herd Behaviour and Cascading in Capital Markets: a Review and Synthesis", *European Financial Management*, 9, 25-66.

Hwang, S., and M. Salmon, 2001. "A new measure of herding and empirical evidence", Working Paper from City University Business School, Available at SSRN.

Ibbotson, R. G., and P. D. Kaplan, 2000. "Does asset allocation policy explain 40, 90, or 100 percent of performance?", *Financial Analysts Journal*, 56(1), 26-33.

Jones, S. L., D. Lee, and E. Weis, 1999. “Herding and feedback trading by different type of institutions and the effects on stock prices”, Working Paper of the Kelley School of Business, Indiana University.

Lakonishok, J., A. Shleifer, and R. W. Vishny, 1992. "The impact of institutional trading on stock prices", *Journal of Financial Economics*, 32(1), 23-43.

OECD, 2007. *Pension Markets in Focus, Issue (4)*. OECD, Global Pension Statistics.

Oehler, A., 1998. "Do mutual funds specializing in German stocks herd?", *Finanzmarkt Und Portfolio Management*, 12(4), 452-465.

Sharpe, W. F., 1992. "Asset allocation: Management style and performance measurement", *Journal of Portfolio Management*, 18(2), 7-19.

Voronkova, S., and M. T. Bohl, 2005. "Institutional traders' behavior in an emerging stock market: Empirical evidence on polish pension fund investors", *Journal of Business Finance & Accounting*, 32(7/8), 1537-1560.

Wermers, R., 1999. "Mutual fund herding and the impact on stock prices", *The Journal of Finance*, 54(2), 581-622.

Wylie, S., 2005. "Fund manager herding: A test of the accuracy of empirical results using U.K. data", *The Journal of Business*, 78(1), 381-403.